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6. AUTHOR(S)

Prof. Jun Tani

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

KAIST(Korea Advanced Institute of Science and Technology)
291 Daehak-ro, Yuseong-gu
Daejeon 305-701
Korea

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"Studies on a Novel Neuro-dynamic Model for Prediction Learning of Fluctuated Data Streams: Beyond Dichotomy between Probabilistic and Deterministic Models"

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Prof. Jun Tani
tani1216jp@gmail.com
Dept. of Electrical Eng., KAIST
291 Daehak-ro (373-1 Guseong-dong), Yuseong-gu, Daejeon 305-701, Republic of Korea
Tel +82-42-350-7428

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Abstract

The proposed study investigates a novel neuro-dynamic model which can learn to predict or regenerate fluctuated sequence patterns by extracting latent statistical structures in the patterns. The novelty of the model is that the fluctuated sequences are learned by adequately incorporating stochastic dynamics and deterministic chaos self-organized in the network. The model is expected to bring the following advantages: (1) adequate mixtures of stochastic dynamics and deterministic one can gain representation power of the model, (2) no needs for arbitrary manipulation of data as well as interpretation of them by human, (3) possibility for scaling of the model by incorporating with the scheme of multiple timescales dynamics for extracting temporal hierarchy from the data. The potential impacts by applying the model to sensory-motor sequence learning by robots as well as video image understanding by accumulated learning of the exemplars are discussed.

1. Introduction

Capability for learning to predict perceptual streams or encountering events by acquiring internal models is indispensable for intelligent or cognitive systems because various cognitive functions are based on this compentency including goal-directed planning, mental simulation and recognition of the current situation. Learning to predict is a difficult task because time-developments of physical systems are often observed as noisy or fluctuated. In such situations, with assuming that the phenomena are probabilistic, model estimation based on probabilistic model are performed. By

partitioning the system's state space into a finite set of discrete states with labels, probabilistic state transition models for the system dynamics can be acquired by counting events of each state transition as shown in the Hidden Markov Modeling scheme. However, it is not trivial to determine if the observed fluctuated time series data are truly generated by some statistical mechanisms especially when the amount of observed data are not enough. This is because it might be still possible that the observed phenomena are just "pseudo stochastic" by meaning that they are actually generated deterministically by means of the initial sensitivity characteristics of chaos which is mechanized in the original continuous state space. Such examples can be seen in the studies of deterministic neuro-dynamic models (Tani & Fukumura, 1994; Nishimoto & Tani, 2005; Namikawa et al, 2011).

Although there has been a dichotomy between determinism and non-determinism of allowing probability in modeling complex phenomena, such dichotomy may not be essential when biological brains or artificial cognitive agents attempt to develop internal models of the world via accumulated direct observation or perceptual experiences. If deterministic chaos or a particular statistical mechanism is necessary to model a set of observed phenomena, either mechanism could be *self-organized* in the course of developing the model rather than given *a priori*. The mechanism self-organized via accumulated learning could turn out to be a merging of deterministic chaos and stochastic dynamics rather than one of them.

The primary motivation of the research is to examine how these two mechanisms can incorporate in developing effective models to account for observed temporal phenomena. This research trial could lead to (1) an opening of a new theory for handling fluctuated data which is beyond traditional statistical theory of assuming law of large number, (2) an invention of a novel but much simpler computational scheme which can learn to predict as well as recognize observed fluctuated data in continuous space and time domain by utilizing self-organization mechanisms of neuro-dynamic systems.

The current study utilize a dynamic neural network model, so-called the stochastic continuous time recurrent neural network (S-CTRNN) model (Murata et al., 2013) which was developed in our laboratory previously. The current research investigates the aforementioned problems by extending this model. Next section will introduce the basic mechanism of S-CTRNN model and explain how it can be extended for possible applications for the current problem.

2. The stochastic CTRNN model and its extension

Model

Here, we describe the basic mechanism of S-CTRNN model (Murata et al., 2013) which can learn to extract probabilistic structures latent in a set of exemplar sequence patterns with particular fluctuations. This model is built on the conventional CTRNN model which is characterized by so-called its context loop consisting of context input units c_t and context output units c_{t+1}. The context output units employ the dynamic of leaky integrator neuron with decay rate of $(1-\tau)$ where τ is time constant. The S-CTRNN is characterized by its capability of predicting subsequent inputs not only with their means but also with their variances (see Fig.1).

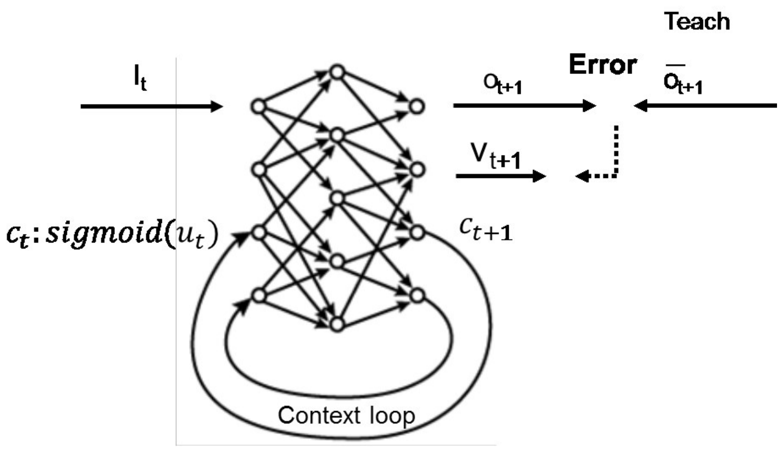


Fig.1 S-CTRNN model

This implies that if some parts of the input sequences are more fluctuated than other parts, the time-dependent variances in these periods become larger. On the other hand, if some parts are less fluctuated, their variances become smaller. It can be said that S-MTRNN can predict own predictability for each dimension of the input sequences in a time-dependent manner. The network model trained can reconstruct the target fluctuated sequences in terms of stochastic dynamics by adding noise with the estimated time-varying variance to the predicted mean of the output at each step. For the purpose of learning to predict both average and variance of each dimension of the target sequences, the following likelihood function L_{out} is maximized.

$$L_{out} = \prod_r \prod_t \prod_i \frac{1}{\sqrt{2\pi v_{r,t,i}}} exp\left(-\frac{\left(o_{r,t,i}-\bar{o}_{r,t,i}\right)^2}{2v_{r,t,i}}\right) \qquad \text{(Eq. 1)}$$

where $o_{r,t,i}$ is the *i*th dimension of the prediction output at time step t in the *r*th sequence, $\bar{o}_{r,t,i}$ is its teaching target, and $v_{r,t,i}$ is its predicted variance. Eq. 1 is to

minimize the square error divided by estimated variance at each step. This means that the prediction error at a particular time step is pressured to be minimized more strongly when its variance is estimated as smaller. Otherwise, the prediction error is minimized less strongly. In the course of iterative learning with a set of target sequences, this likelihood function is maximized by optimizing connectivity weights and the initial context states estimated for all corresponding target sequences. After iterative learning for maximizing L_{out}, the target sequences can be reconstructed by means of stochastic dynamics parameterized by the time-varying variance estimated by the model.

Now, we explain an extension of the S-CTRNN model for the purpose of investigating the dichotomy between the stochastic model and the deterministic dynamics model. As it is well known that deterministic chaos develops by utilizing the initial sensitivity characteristics of nonlinear dynamic system. Therefore, we hypothesize that a particular control of the initial sensitivity in the network dynamics during the learning process could manipulate development of chaotic dynamic structures in the network. Our intuition is that if the initial sensitivity is positively utilized by allowing large variability in the distribution of the initial context states to be determined in the course of learning, fluctuations in the target sequences could be represented by developing deterministic chaos while minimizing estimation of the output variances. Otherwise, the fluctuations could be reconstructed as driven by noise term of which variance is estimated with relatively large value. By following this idea, an additional likelihood functions L_{init} is considered which controls the distribution of initial context unit states determined for the set of target sequences.

$$L_{init} = \prod_r \prod_i \frac{1}{\sqrt{2\pi\sigma_{IS}^2}} exp\left(-\frac{\left(\tilde{u}_i - u_{r,0,i}\right)^2}{2\sigma_{IS}^2}\right) \quad \text{(Eq. 2)}$$

where σ_{IS}^2 is the predefined variance that confines variability of a set of the initial context unit states for all teaching target sequences, $\tilde{u}_i$ is the optimized mean of the *i*th dimension internal value of the initial context unit states among all sequences, and $u_{r,0,i}$ is the *i*th dimension initial state for the *r*th sequence. Eq. 2 is to put specific probabilistic distribution constraints on determining the optimal initial context states for all sequences with the parameter σ_{IS}^2. If the σ_{IS}^2 is set with a large value, the distribution of the initial context states becomes wide. Otherwise, it becomes tight. In the proposed extended model, the following likelihood function $InL_{all} = InL_{out} + InL_{init}$ is maximized. By maximizing the likelihood L_{all} during the learning process, optimal connectivity weights common to all target sequences, the initial state for each target sequence and the estimates of time-dependent variance for each sequence are

obtained depending on the parameter σ_{IS}^2.

Learning to reconstruct stochastic FSM

In the following simulation experiment, we test the model with an example of learning to reconstruct a particular stochastic finite state machine (S-FSM) from the exemplar sequences (see Fig.2.)

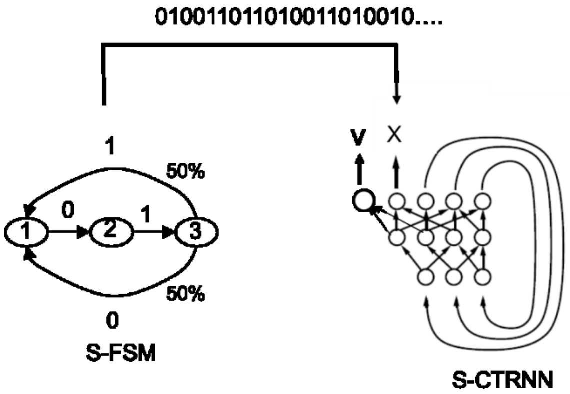


Fig.2 Learning to reconstruct a target S-FSM by a S-CTRNN model

The target S-FSM generates deterministic sequence of "0, 1" in the state transition from the state 1 to state 3 whereas it generates 0 or 1 with equal probability in the state transition from the state 3 to the state 1. S-CTRNN with 10 context units, 12 hidden units and two output units, one for prediction of the mean and the other for the estimation of variance is utilized for learning target sequences generated by the target S-FSM. The time constant τ is set as 1.0. This means that CTRNN used in the experiment turns out to be an RNN with discrete time operation. The target sequences consist of 10 sequences each of which is generated with 25 step length. The same target sequences are learned with two different learning conditions, so-called the narrow initial states distribution with setting σ_{IS}^2 as 0.001 (Narrow IS) and the wide initial state distribution with setting σ_{IS}^2 as 1.0 (Wide IS).

Fig.3 (a) and Fig.3 (b) show the reconstruction of the target with the network model trained under the narrow initial states distribution and the wide one, respectively.

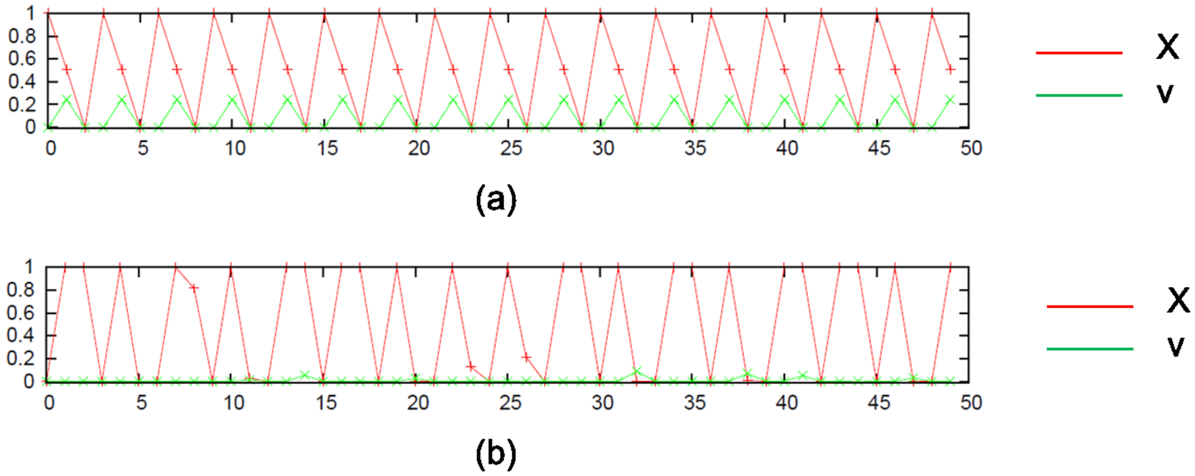


Fig.3 Output sequences with X: predicted mean and V: estimated variance with (a) the Narrow IS case and with (b) the Wide IS case.

It the narrow distribution case in Fig.3(a), we can see 3 steps length periodic sequence pattern of repeating 0.0, 1.0, 0.5 in the out of mean value and 0.0, 0.0, 0.25 in the output of variance estimation with synchronization. This corresponds to the deterministic state transitions from the state 1 to the state 2 and to the state 3 and probabilistic one returning to the state 1 in the target S-FSM. We can see that the underlying probabilistic structure of the target S-FSM is well reconstructed in the trained model in terms of stochastic dynamics. On the other hand in the wide distribution case, we can see the repetitions of 3 steps sequence composed of 0.0, 1.0, "?" in which "?" comes either close to 1.0 or to 0.0 seemingly at random in the output of mean whereas the output of variance estimation becomes almost zero. This implies that the sequences are reconstructed in terms of deterministic dynamic system. Actually, development of deterministic chaos was confirmed by observing a positive value for the maximum value of Lyapunov exponents through the analysis of the obtained dynamic trajectories. These simulation results show that the extended S-CTRNN can learn to imitate the output sequences of S-FSM by reconstructing them either in stochastic dynamics or deterministic chaos depending on the learning condition imposed on the initial sensitivity characteristic of the network dynamics.

Learning to imitate movement patterns generated with probabilistic decision sequences.

In the real world situation, perceptual sequences could be continuous in time and also they could be hierarchically organized. An interesting question might be how the

network model can learn to extract latent probabilistic decision structures in the higher cognitive level of other agents from its lower level continuous perceptual experience. On the purpose of investigating this problem, we performed robot experiments using a humanoid robot “NAO”. For the robot task, the robot learns to imitate tutor guided behaviors including probabilistic switching between different action primitives. For the current robotics experiment, S-CTRNN model was further extended such that it can deal with multiple timescale property as shown in our prior study on multiple timescale recurrent neural network (MTRNN) model (Yamashita & Tani, 2008). Our speculation is that a newly proposed model of S-MTRNN can learn to predict hierarchically organized fluctuated patterns by utilizing the multiple timescales property. The proposed S-MTRNN (Fig.4) contains two clusters of the fast context units (c^F) with smaller τ and the slower context units (c^S) with larger τ. It receives the current proprioception state (the encoder readings of 4 DOF joint angles) and generates the one in next time step in continuous manner. Number of the fast context units and the slow context units employed were 30 and 10, respectively. The time constant τ was set as 5 for the fast context units and 30 for the slow ones.

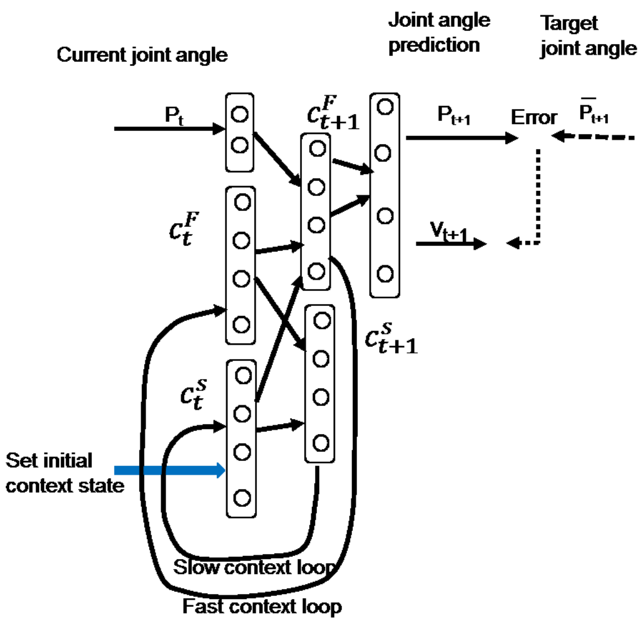


Fig. 4 S-MTRNN model.

During the tutoring session for NAO robot, the experimenter tutored two types of arm movement actions, one for moving the arm to the left-hand side and then returning back to the center position and the other for moving the arm to the right-hand

side and then returning back to the center position by repeating them in random orders in sequences (Fig. 5).

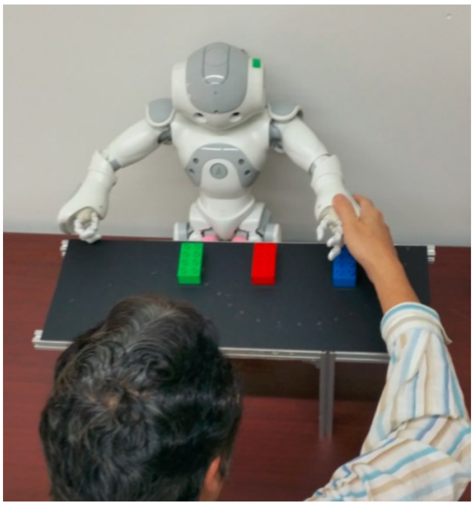


Fig.5 Tutoring of NAO robot by direct guidance. Repeatedly guiding two different arm movements in arbitrary sequential combination, one from center (red block position) to left (green block) and the other from center to right (blue block).

Each tutoring trial consists of 5 successive switching and all trials cover all possible combinations of 2^5 sequences. In the training of the S-MTRNN with the tutoring patterns, the training was repeated twice with setting σ_{IS}^2 with a small value and a large value in order to generate a narrow initial state distribution (Narrow-IS) and a wide initial state distribution (Wide-IS), respectively. After the training of the S-MTRNN was completed, the robot movement was generated for both training cases by means of the so-called closed-loop operation. In the closed-loop operation with the S-MTRNN, a Gaussian noise with the estimated variance at each step is added to the feedback from previous step prediction outputs to the current step input.

Fig. 6 (a) and (b) illustrate examples of behavior generation in terms of the proprioception sequence associated with the estimated variance and the internal neural activities in the fast and the slow context units generated by the network trained under Narrow-IS and Wide-IS conditions, respectively.

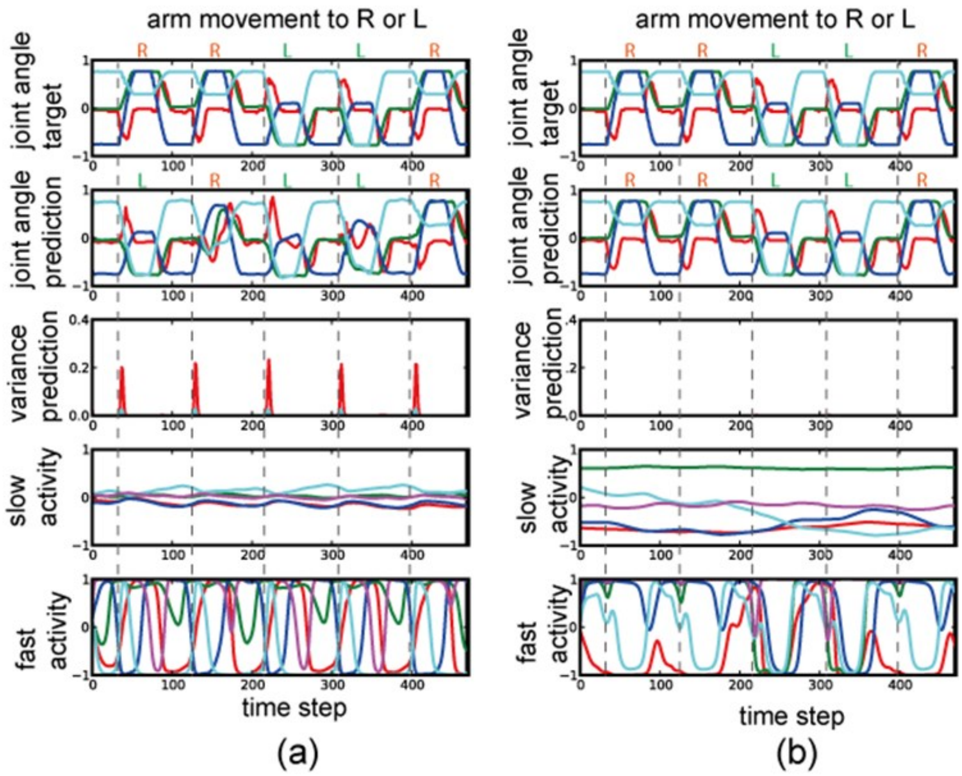


Fig. 6. The robot behavior generation (a) in Narrow-IS case and (b) in Wide-IS case.

In both cases, it can be observed that two behaviors of moving to right or moving to left are alternated arbitrarily. In the Narrow-IS case, the estimated variances showed their sharp peaks at the decision points but almost zero at other time steps. This implies that the trained S-MTRNN developed action primitives of moving to left and right as two distinct chunks and their probabilistic switching mechanism at the decision points by utilizing the estimated large variance in those time points. Therefore, it can be said that probabilistic decision mechanism was developed in the training condition of Narrow-IS. On the other hand in the Wide-IS case, the variance is estimated as almost zero for all steps including the decision point. This implies that motor behavior is generated as an initial sensitive deterministic dynamics in the Wide-IS condition. Although we expected the development of chaos again in this experiment, the largest Lyapunov exponent turned out to be negative which denied our expectation. However, we observed that seemingly random switching at the decision point continues more than 10 consecutive switching times before converging into a particular periodic sequence. This implies that spontaneous switching was mechanized by transient chaos. For relatively long period, arbitrary sequential combinations of two action primitives can be generated depending

on the initial context state.

Another interesting observation was that the internal neural activity was observed as quite different between the two cases. In the Narrow-IS case, the neural activities in both of the slow and the fast subnetworks showed the same values for all decision points. On the other hand in the Wide-IS case, both of the slow and fast neurons exhibit specific activation patterns at each decision point which can predict the forthcoming behavior of either moving to left or right. This implies that there was no bias in the neutral activity at the moment of the decision in the Narrow-IS case whereas there were top-down predictive biases represented with specific neural activation patterns in the decision points in the Wide-IS case. Finally, we consider contribution of the multiple timescale property of the employed model to the imitative learning of hierarchically organized probabilistic decision behavior. Our additional experiments revealed that the network model without the slow context units could learn the task with the Narrow-IS condition but not with the Wide-IS condition. The slow dynamic part was necessary in the Wide-IS condition because transient chaos which enables spontaneous switching of the primitive actions stored in the fast dynamics part was developed in the slow dynamics part.

The current experiment results showed that S-MTRNN model which is characterized by the multiple timescale property can learn to reconstruct continuous perceptual flow fluctuated as triggered by sequences of probabilistic decisions. It was observed that stochastic dynamic was developed by less utilizing the initial sensitivity characteristics while deterministic dynamic with transient chaos did by more utilizing the initial sensitivity characteristics in the learning processes. This result is analogous to the one shown in our previous simulation experiments on the imitative learning of S-FSM output sequences.

Two-leveled S-MTRNN to extract probabilistic structures latent in different timescales dynamics

We observed several limitations of the S-MTRNN in the second experiment. First, the slow context unit activities were not developed so well in the Narrow-IS condition. Second, although the variance peak generated at each switching point, predicted temporal sequence became sharp at each switching point. One hypothesis is that variance was only connected with fast context units or fast timescale network. That's why variance generation merely depends on fast timescale dynamics. To overcome this limitation, we suggest extended S-MTRNN, called two-leveled S-MTRNN.

Two-leveled S-MTRNN (Fig. 7) consists of two sub-networks, each

characterized by different timescale. Fast timescale network contains fast context units with small time constant. It receives the current input I_t^F to generate the one in next time step as like the S-MTRNN. The fast timescale network connected with newly proposed units, called pseudo target units $\bar{o}_t^S$. Slow timescale network contains slow context units with large time constant to generate pseudo target units in closed-loop phase. It receives the current input I_t^S which comes from pseudo target units for previous time step in training phase.

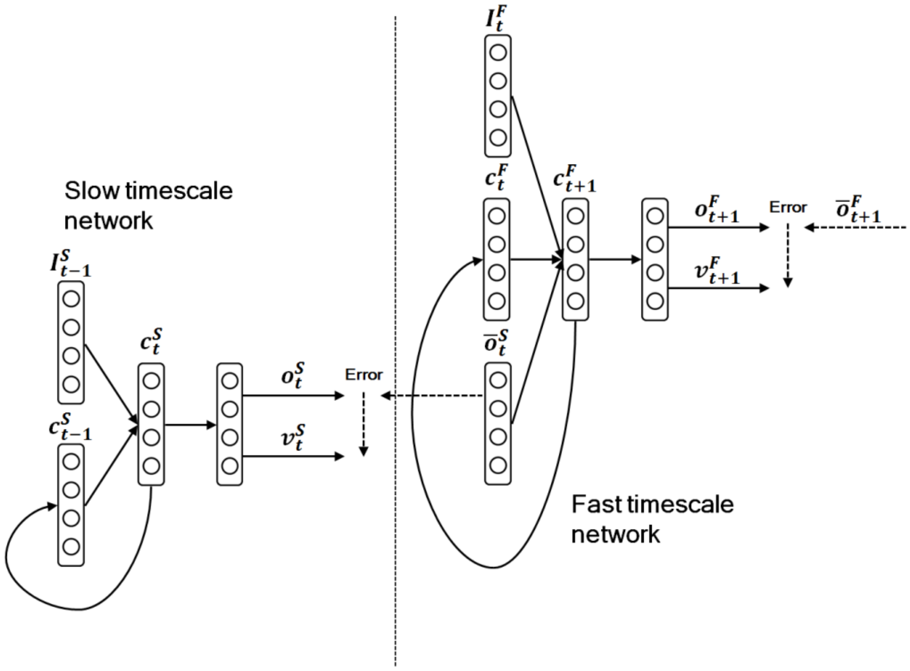


Fig. 7. Two-leveled S-MTRNN model

Unlike the previous models, training phase was separated into two stages as like a mixture of RNN experts (Namikawa, 2008). In first training phase, the fast timescale network trained and the values of the pseudo target units are self-organized while slow timescale network fixed, by maximize the likelihood function L_{fast} defined as follows:

$$L_{fast} = \prod_r \prod_t \prod_i \frac{1}{\sqrt{2\pi v_{r,t,i}^F}} exp\left(-\frac{\left(o_{r,t,i}^F - \bar{o}_{r,t,i}^F\right)^2}{2v_{r,t,i}^F}\right) \qquad \text{(Eq. 3)}$$

where $o_{r,t,i}^F$ is ith dimension of the output of fast timescale network at time step t in the rth sequence, $\bar{o}_{r,t,i}^F$ is its teaching target, and $v_{r,t,i}^F$ is the variance of fast timescale network. The pseudo target play key role in this model by competing with fast output and fast variance. More detail, probabilistic structure latent in slower timescale

dynamics which cannot be properly minimized by fast output and fast variance, can be minimized by self-organizing the pseudo target.

In second training phase, slow timescale network trained by minimizing likelihood function L_{slow} based on trained fast timescale network.

$$L_{slow} = \prod_r \prod_t \prod_i \frac{1}{\sqrt{2\pi v^S_{r,t,i}}} exp\left(-\frac{\left(o^S_{r,t,i}-\bar{o}^S_{r,t,i}\right)^2}{2v^S_{r,t,i}}\right) \qquad \text{(Eq. 3)}$$

where $o^S_{r,t,i}$ is ith dimension of the output of slow timescale network at time step t in the rth sequence, $\bar{o}^S_{r,t,i}$ is the pseudo target self-organized in first training phase, and $v^S_{r,t,i}$ is the variance of slow timescale network. During the second training phase, slow timescale network try to generate the pseudo target by means of slow output and slow variance. By doing that, probabilistic structure which captured by pseudo target, can be redistributed into slow output and slow variance.

To verify the capability of the two-leveled S-MTRNN, we conducted simple decision making experiment using two different computer generated temporal sequences (Fig. 8). Two temporal sequences exactly same until 100 time step. After that one goes down the other goes up. The purpose of the experiment is to see whether probabilistic structure in slow timescale dynamics can be captured by the two-leveled S-MTRNN or not. For this experiment, 30 fast context units with time constant τ set to 5 in fast timescale network and 1 pseudo target unit while 10 slow context unit with time constant τ set to 100 in slow timescale network. The two-leveled S-MTRNN trained with two different training conditions: (1) updating initial context state (deterministic case) and (2) fixed initial context state (stochastic case).

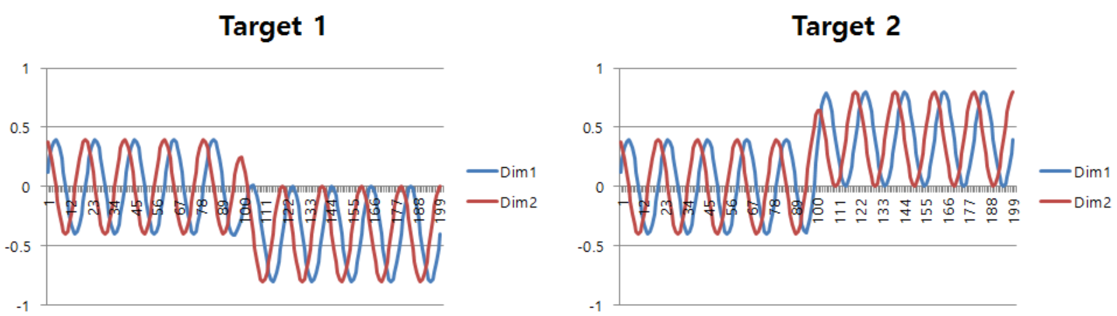
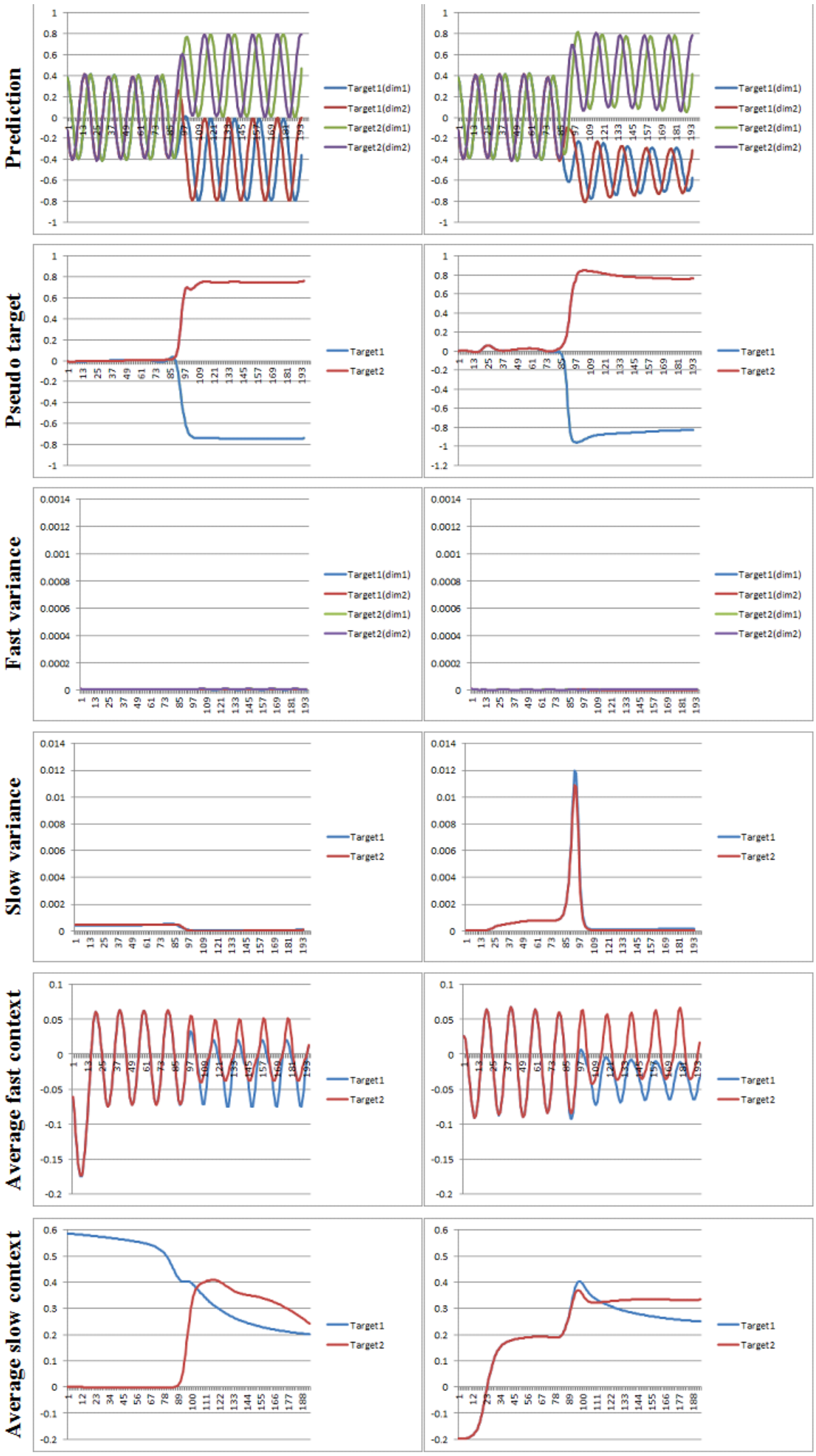


Fig. 8. Computer generated 2-dimensional branching sequences



(a) (b)

Fig. 9. The internal dynamics of the two-leveled S-MTRNN (a) in deterministic case and (b) stochastic case.

In Fig. 9, self-organized structures of the pseudo target were similar while fast variance was almost zero regardless of training conditions. It means slow probabilistic structure within temporal sequences, such as branching prediction, can be more easily extracted by the pseudo target rather than fast output and fast variance. The significant difference between training conditions comes in slow timescale networks. In the deterministic case, each initial state of the slow context for each target sequence is totally separated and slow variance was almost zero. These results showed that network already knew the direction of branching from the starting point in terms of initial state of slow context. This result is analogous to the robotics experiment results shown in (Tani, 2014). On the other hand, in the stochastic case, network cannot predict the direction of branching because the initial state of the context was exactly same. But, network can predict branching point through slow variance peak generation at branching point. In brief, the pseudo target extract slow probabilistic structure in the first training phase, and then slow probabilistic structure extracted by the pseudo target, was re-extracted by the slow timescale network in stochastic dynamics or deterministic dynamics depends on training conditions in the second training phase. At the same time, in stochastic case, predicted temporal sequence showed smooth transition in the closed loop generation. Because generated noisy of the slow variance added to slow context dynamics, not directly added to fast context dynamics. The simulation results in this experiment indicate the two-leveled S-MTRNN successfully extract slow probabilistic structure in slow timescale dynamics especially thanks to the pseudo target.

3. Summary

The current study investigated a novel neuro-dynamic scheme by which fluctuated sequence patterns generated by particular target sources can be reconstructed by extracting latent statistical structures in the target patterns via iterative learning. The uniqueness of the proposed scheme is that the fluctuated sequences are learned by adequately incorporating stochastic dynamics and deterministic chaos self-organized in the network depending on the initial sensitivity condition set in the learning processes. If the initial sensitivity is utilized in the Narrow IS condition, non-zero value for time-varying variance is estimated along with the prediction of the mean of the target at each step. The target sequence is regenerated in terms of stochastic dynamics because the sequences are generated by adding noise of the estimated variance to the predicted mean at each step. On the other hand, if the initial sensitivity is not utilized, deterministic dynamic of chaos or transient chaos is developed by estimating the time-varying variance as zero for all steps.

The aforementioned principle was well evaluated by conducting a set of experiments associated with a series of extensions in the basic model. The first simulation experiment showed that how the basic model of S-CTRNN can learnt to reconstruct of a target S-FSM by extracting its probabilistic structure. It was shown that the state transition with probabilistic branching in the target S-FSM could be imitated by means of estimating adequate variance at the branching step in the result of learning with the Narrow-IS condition or by developing deterministic chaos with the Wide-IS condition.

The second experiment with utilizing a robot showed that how the extended model of S-MTRNN can learnt to reconstruct continuous perceptual sequences which are generated by particular probabilistic decision sequences. It was shown that S-MTRNN learned two different action primitives by utilizing the fast context unit activities in both of the Narrow-IS and the Wide-IS conditions. However, the mechanism of the probabilistic switching between these primitive actions was developed differently between these two conditions. In the Narrow-IS condition, it was observed that the time-varying variance was estimated with a peak value at each moment of the switching decision. It seemed that the activity in the slow context units contributed less to the whole system performance. On the other hand in the Wide-IS condition, it was found that the probabilistic switching between two primitive actions was mechanized by the transient chaos developed in the slow context activity. One question was arisen by obtaining this result. The question is why the slow context unit activity cannot be utilized in the Narrow-IS condition. If the switching decision is originated by the fluctuation in the higher cognitive level, such fluctuation should appear also in the slow dynamic part in the higher level in the model.

The third simulation experiment was conducted in order to investigate this problem. The two-level S-MTRNN trained to regenerate two branching sequences under two different conditions: stochastic case and deterministic case. The training phase divides into two sub-training phase. In first training phase, fast timescale network was trained while self-organizing the pseudo target. There was no significant difference between two training conditions in this phase. In second training phase, slow timescale network was trained using trained fast timescale network and the pseudo target. Two training conditions were differentiated in second training phase. Probabilistic structure extracted by the pseudo target can be re-extracted by initial context state or slow variance depends on training condition. As we expected, the two-leveled S-MTRNN utilized slow context dynamics and generated smooth transition of predicted temporal sequence, even if in stochastic case. But, the two-leveled S-MTRNN has been still in

preliminary stage and requires further studies. For the future work, we will provide updated version of the two-leveled S-MTRNN which can train fast timescale network and slow timescale network at the same time.

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